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A Multi-objective Optimization of Broadband WMN: Energy - Capacity Tradeoff and Optimal System Configuration

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Abstract: This paper is focused on broadband wireless mesh networks based on OFDMA resource management. We develop an extensible linear programing model using column generation to compute power efficient schedules with high network capacity. We adopt a more realistic model for the physical layer using SINR model with a fine tuned power control at each node. Correlation between capacity and energy consumption is analyzed as well as the impact of physical layer parameters - SINR threshold and path-loss exponent. We highlight that there is no significant tradeoff between capacity and energy when the power consumption of idle nodes is important. Furthermore, we include an adaptive modulation in each node combined with a variable transmission rate to find an optimal system configuration of the network. We also study the impact of power control, spacial reuse and adaptive modulation on capacity and energy consumption and we give some network engineering results.

Key-words: Mesh networks, capacity, energy, scheduling, multi-objective analysis, resource allocation.

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Optimisation multi-objectif des réseaux maillés sans fil à large bande: Compromis énergie-capacité et configuration optimale du réseau

Résumé : Dans ce papier, nous nous intéressons aux réseaux maillés sans fil à large bande utilisant la technique OFDMA pour l'allocation de ressources. Nous développons un programme linéaire pour calculer une configuration optimale du réseau efficace en énergie et avec un maximum de capacité. Vue la complexité du programme linéaire, nous utilisons la technique de génération de colonnes pour résoudre le problème. Nous implémentons un modèle de couche physique plus réaliste utilisant un modèle d'interférences avec un contrôle fin de puissance à chaque noeud. Nous étudions le compromis entre la capacité du réseau et la consommation d'énergie ainsi que l'impact de deux principaux paramètres de couche physique (seuil SINR et coefficient d'affaiblissement). Nous montrons que le compromis entre la capacité et la consommation énergétique est faible lorsque la consommation d'un noeud en état de veille est importante. Ensuite, nous ajoutons une modulation adaptative à chaque noeud pour calculer une configuration optimale du réseau. Nous étudions l'impact du contrôle de puissance, de la réutilisation spatiale et la modulation adaptative sur la capacité et la consommation d'énergie.

Mots-clés : Réseaux Radio Maillés, capacité, consommation énergétique, multiobjectif, allocation de ressource.

1 Introduction

High data rate is a challenge for the next generation cellular networks. This objective needs a significative densification of cells which requires an efficient backhauling infrastructure. We consider a broadband wireless mesh network (WMN) based on OFDMA resource management and composed of a twofold architecture: *i)* clients are connected to base station (BS) and *ii)* a wireless backhaul topology interconnects the BS with the core network. These BSs are equipped with routing functionalities and communicate together through radio links, as in LTE-Advanced relay or WIMAX Mesh [**?**, **?**, **?**]. The BS collect the traffic generated by the mobile clients and forward it through multi-hop communications to some dedicated BS, denoted gateways, that bridge the backhauling network to the core network (Fig. 1). We assume that mobile-to-BS and BS-to-BS traffics use different and independent resources. In this work, we focus on the backhauling network and we do not take into account the users requests but rather their flows aggregated by the BS.

Optimizing the network capacity is one of the main research issues for WMNs since the seminal work of Gupta and Kumar [**?**] where asymptotic capacity is linked to the size of the network. Besides, minimizing the energy expenditure and electromagnetic pollution of such infrastructures are hot societal and economical challenges nowadays (see EARTH, CARMEN european projetcs)[1].

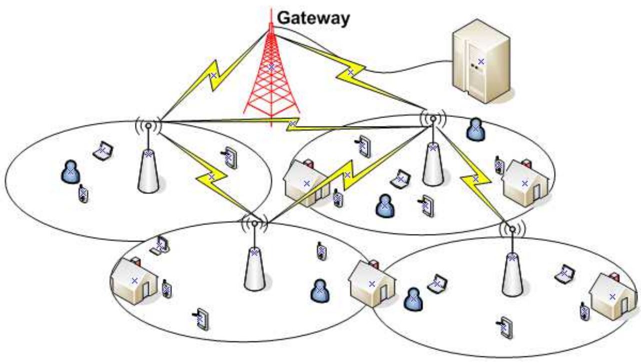


Figure 1: Wireless mesh network architecture: base stations collect the traffic from clients (mobile or static) and forward it to the core network.

The first contributions of this work is to develop a flexible (extensible) multi-objective optimization framework. This framework is used to calculate an optimal system configuration of the backhauling network when the objective is to compute high network capacity with minimum energy consumption. We mean by system configuration the complete choice of parameters for operating the backhauling network. To maximize the network capacity and to minimize the energy consumption are the main goal of this work. As these two objectives appear to be antagonistic to each other, it is important to investigate the tradeoff between them.

In order to better understand and to minimize the complexity of the multi-objective linear program, we begin our study by some hypothesis. We first

[1] EARTH: https://www.ict-earth.eu/, CARMEN: http://www.ict-carmen.eu/

assume that all BSs use a single transmission power and a single modulation and coding scheme. We then extend this study by including a Signal-to-Noise-and-Interference-Ratio (SINR) based model with fine tuned power control at each node [**?**]. This allows us to investigate deeply on the capacity/energy tradeoff and to study the impact of physical layer parameters such as the SNR threshold and the path-loss exponent on these metrics. Finally, we show how to extend this study with an adaptive Modulation and Coding Schemes (MCS) jointed with power control. We study the impact of these additional mechanisms on the performance of the network.

The rest of paper is organized as follows. Section 2 reviews related works. Section 3 gives an overview about OFDMA and presents the problem statement and the network model. Then, we present our multi-objective framework based on a linear program and a column generation. Section 5 investigates the case of fixed transmission power and single modulation. Section 6 study the impact of physical layer parameters, and the tradeoff between energy consumption and capacity. Next we extend this study by including an adaptive MCS jointed with power control. Section 8 investigates the impact of traffic demand and topology on the energy-capacity tradeoff. Finally, we discuss about the main contributions of this paper and we compare with others works.

2 Related work

There exists a vast amount of literature devoted to improve the capacity of WMN and to minimize the energy consumption of multi-hop wireless network. Most of these studies have addressed these two issues separately. To increase the throughput provided to nodes, several studies have investigated the TDMA scheduling techniques, i.e. to identify sets of links that can be simultaneously activated [**?**, **?**, **?**, **?**]. [?] is focused on the scheduling problem around an access point on 802.11 networks. It investigates the Round Weighting Problem (RWP) trying to determine the minimum number of rounds (a round is any set of pairwise disjoint edges). [?] studies the problem of routing and call scheduling in 802.11 multi-hop wireless networks and provide an optimal framework for determining optimal routing and scheduling needed by the traffic in the network using a binary interference model and fixed transmission power. In a practical system, transmission power is an important tunable parameter for reliable and energy efficient communication, because higher transmit powers can increase the SINR at the receiver to enable successful reception on a link, and lower transmission power can mitigate interference to other simultaneously utilized links. In [?], a joint scheduling, routing and power control strategy is proposed. The authors develop a computational tool using column generation to maximize the minimum throughput among all flows. They highlight the usefulness of the power control on the performance of multi-hop wireless networks.

The joint problem of power control and scheduling link transmissions in a wireless network in order to optimize performance objectives (throughput, delay, energy), received a lot of attention in the recent years [**?**, **?**, **?**]. In [?], the problem of finding a minimum-length schedule that satisfies a set of specified traffic demands is addressed, using a column-generation-based method. It is shown that power control improves the spatial reuse, which leads to further decrease of the schedule length compared to a fixed transmit power. Because scheduling with power control using a SINR model is NP-hard [?, ?], several papers proposed heuristic algorithms to minimize the schedule length and the energy consumption with and without power control [?, ?].

The optimization of energy consumption also has been well addressed in the literature especially in sensor networks where a sensor has a limited battery power. The wireless radio is the most energy consuming unit of a sensor node. It can work in one of four different states: transmit (Tr), receive (R), idle (I) and sleep (S) [?, ?]. However, the energy expenditure in a node is typically dominated by the transmission unit. From the energy efficiency standpoint, the most effective solution is to put the wireless nodes in sleep mode [?, ?]. In [?] the authors consider the problem to find the minimum energy needed to schedule a given set of transmissions within a predefined number of slots.

To the best of our knowledge, only very few papers investigate on both the study of capacity and energy consumption. [?] studied energy, latency and capacity trade-offs existing in a multi-hop ad-hoc wireless network. The authors assume a linear topology with a simple energy model. They propose an analytical study that does not take into account a realistic interference model. The tradeoff between energy consumption and capacity is investigated using a binary interference model and a fixed transmission power in [?]. The relation between energy minimization and through-put maximization of a 802.11 WLAN is analyzed in [?]. [?] studied the tradeoff between throughput and lifetime on a multi-hop wireless network. It is shown that the optimal tradeoffs are usually not obtained at the minimum power that enables network connectivity. This tradeoff is like presented in this paper since the improving of the network lifetime is feasible by the minimizing of the energy consumption.

[?] have investigated the problem of the joint allocation of modulation and coding (MCS), resource blocks and power assignment to users in LTE system, while minimizing the overall power consumption. To achieve this objective, the authors break down the problem in two loops based on a linear program and a metaheuristic algorithm. It is shown that to provide a minimum bit rate to user, it is better to use more resource blocks with lower MCS and less power, rather than only use few resource blocks with higher MCS and more power.

The lack of joint study of the capacity and energy consumption in the literature leads us to study them accurately. We will focus in particular on the tradeoff between them after presented the necessary tools to do it.

3 Resource allocations and problem definition

3.1 Resource allocations

In this work, we focus on broadband WMNs based on OFDMA resource management. An example of technologies using this technique is LTE-Advanced, WIMAX and HSDPA. We illustrate our study with a prototype of LTE like frame structure detailed in the following. Nevertheless, the optimization models that we present further on are generic and can be applied to any synchronous slotted technology in which the resource is divided into time-frequency elements.

LTE radio transmission is based on Orthogonal Frequency Division Multiple Access (OFDMA) for downlink communications and Single Carrier Frequency Division Multiple Access (SC-FDMA) for uplink communications. OFDMA allows to exploit multiuser diversity and to provide more flexibility in radio resources allocation.

As in LTE, we consider a frame divided in 20 time-slots where the duration of one time-slot is 0.5ms (TDD mode). Two adjacent time-slots are grouped into a sub-frame of length 1 ms, corresponding to a Transmission Time Interval (TTI). Each time-slot corresponds to 7 OFDM symbols, which is preceded by a cyclic prefix to avoid inter-symbol interference. The bandwidth corresponding to a slot (7 OFDM symbols) is subdivided into several blocks of 12 subcarriers, each of which is called Physical Resource Block (PRB). The smallest resource unit that can be allocated to a user covers a TTI of 1ms and a PRB (bandwidth of 180 khz), called scheduling bloc (fig. 2).

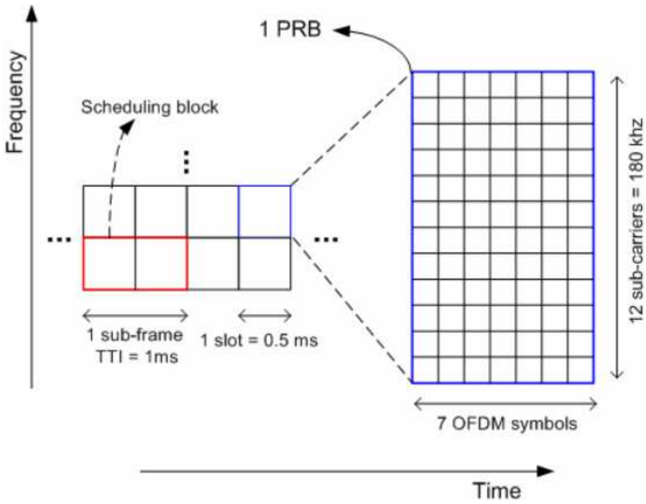


Figure 2: An illustration of resource element in LTE

3.2 Problem definition and assumptions

We consider a slotted, synchronized WMN and static topology and demand. Hence it is reasonable to assume that the network is periodic with period T. We assume that each base station is equipped with omni-directional antennas. The transmission power can be adjusted continuously within a given interval. All base stations periodically send a given quantity of traffic which represents the aggregate demand of their clients: these traffics require several scheduling blocks to be transmitted. The traffic is routed to gateways through multi-hop paths to be computed. Note that in our study the traffic demand can be a uniform demand (each BS have the same demand) or a random demand (Poisson process or uniform distribution).

We assume that each scheduling block can be assigned with a transmission power and MCS. Given a bandwidth available for the backhauling network, the goal is to find an optimal node setup (transmission power and Modulation and Coding Scheme (MCS)) and a schedule within a minimum time frame to maximize the capacity. Our framework allocates, for each base station, the optimal number of scheduling bloc in order to send its own traffic and forward the traffic of the other nodes.

3.3 Network model and notations

The fixed infrastructure of the WMN can be model as a directed graph G(V,E). The set V_{BS} represents the set of base stations, and V_g the set of gateways ($V = V_{BS} \cup V_g$). In the following, we present some metrics and notations useful for the remainder of the paper.

Network capacity Each BS of V_{BS} routes to the gateway an aggregated demand d_v. We consider a stationary network, periodic, of period T. The network capacity of the WMN, defined as the ratio between the total traffic received at the gateways and the period length to collect it, is $\frac{\sum_v d_v}{T}$. Therefore, to optimize the capacity is to minimize the number of time slots used to activate the links transmitting the traffic. An insight of a throughput-optimal scheduling policy would be to pack as many links as possible in each time slot, that is maximizing the spatial reuse of system resources. This objective has to be mitigated with interference and energy consumption constraints.

Link conflict model The set of edges $E \subseteq V \times V$ corresponds to the communication links. A (directed) link $(u, v) \in E$ exists if and only if the sender node u can communicate directly with the receiver node v. We denote (u,v,k) a transmission between nodes u and v on PRB k. This transmission is successful only if the SINR at the receiver exceeds a minimum threshold β, depending on some parameters like bit-error-rate (BER), the modulation, and the coding schemes used. Let $P_t(u)$ denotes the transmission power of the sender u. We assume that the power received at v depends of the attenuation function, denoted $L(u, v)$, which depends of both the distance $d(u, v)$ and the environment. In this paper we will use the classic path-loss attenuation $L(u, v) = d(u, v)^{-\alpha}$ where α is the path loss exponent, but any other propagation model can be used. The SINR condition at receiver v in the PRB k and in the presence of other transmissions is expressed by the following equation:

$$SINR_{(u,v,k)} = \frac{P_t(u) * L(u, v)}{\mu_v + \sum\limits_{(u',v',k) \neq (u,v,k)} P_t(u') * L(u', v)} \geq \beta_v, \tag{1}$$

where $\mu_v \in \mathbb{R}^+$ represents the thermal noise at the receiver.

Definition 1 A set of transmissions on the same resource block is simultaneously feasible if and only if Eq. (1) holds at all receivers. We define a configuration F as a collection of simultaneously feasible transmissions sets, one per available resource. The set of all possible configurations is denoted $\mathcal{F}$.

Note that this generic definition allows to consider any interference model like binary models (transmissions have to be pairwise non interfering, i.e. on non-conflicting links or on distinct PRBs), or SINR based models. Increasing the cardinality of a configuration ($F \in \mathcal{F}$) strengthens the spatial reuse of the links, which contributes to increasing the throughput.

Energy model In this work we assume that a BS consumes different amounts of energy depending on one of three different states: transmit (Tr), receive (R) and idle (I). The first one (Tr) is expended by the source node during transmission. We assume that the source node spends a *transmitting cost* $j_t^k(u) = (Cst + P_t(u)) * \delta t$, where Cst is a fixed cost of the circuit consumption and δt is the time over which the transmission

Table 1: Network model parameters and notations

E, V	Respectively the set of links and nodes
μ_v, β_v	Thermal noise and SINR threshold
$L(u,v)$	Attenuation function
$P_t(u)$, $j_t^k(u)$	Transmit power and energy consumption of transmitter
$P_r(v)$, $j_r^k(v)$	Power/Energy consumption of receiver
$J_{idle}(v)$	Energy consumption of Idle node
d_v	traffic demand of node v
$\mathrm{F_i}$	Transmissions set that can be activated simultaneously
$\mathcal{F}$	Set of all possible configurations: $\mathcal{F} = \cup_i \mathrm{F_i}$
$c_{(u,v)}^k$	capacity of the link (u,v) on the PRB k
$J_{(u,v)}^k$	energy consumed by the link (u,v) on the PRB k
MCS_j	Modulation and Coding Scheme
CR_j, M_j	Code rate and constellation size of MCS_j
N_{Sym}, N_{Sub}	The number of OFDM symbols and subcarriers

energy is used.
The reception node spends a *receiving cost* $j_r^k(v) = (Cst + P_r(v)) * \delta t$ during reception. In this work we assume that the power consumption of receiver $P_r(v)$ is fixed for all nodes. A node v which is involved in no active transmission is said *idle* and denoted $v \notin \mathrm{F}$, for sake of simplicity. The energy cost of an idle node v is $J_{idle}(v)$. The overall energy consumption of the network is the sum of all node consumption during a time T.

Communication characterization A transmission between nodes u and v on PRB k, (u,v,k), is characterized by the following physical parameters:

- MCS_j: is the Modulation and Coding Scheme assigned to the transmission (u,v,k). A MCS_j is identified by a code rate CR_j and a constellation size M_j. This MCS_j must satisfy a SNR threshold (β_j) to activate the transmission (u,v,k).
- $c_{(u,v)}^k$: is the capacity of the link (u,v) on the PRB k. This capacity depends on the MCS_j assigned to (u,v,k), $c_{(u,v)}^k = \frac{CR_j log_2(M_j)}{T_A} N_{Sym} N_{Sub}$, where T_A is the sum of OFDMA symbol duration (or activation time of (u,v,k)), N_{Sym} and N_{Sub} are , respectively, the number of OFDM symbols and the number of subcarriers.
- $J_{(u,v)}^k$: is the energy consumed for communicating on the link (u,v) on the PRB k. u spends a *transmitting cost* $j_t^k(u)$ while v spends a *receiving cost* $j_r^k(v)$, $J_{(u,v)}^k = j_t^k(u) + j_r^k(v)$.

4 Multi-objective optimization: Capacity Maximization and Energy Consumption Minimization

Maximizing the number of simultaneous transmissions allows to minimize the time frame (total slot number), i.e. to maximize the capacity. Unfortunately, it leads to an higher total transmission cost because maximizing the concurrent transmissions

Table 2: Notation for Problem Formulations

$e = (u, v)$	Link with u the sender and v the receiver
d	traffic demand
$J(\text{F})$	Total energy cost for F
$w(\text{F})$	Activation time of F
P, $\mathcal{P}$	Path and Set of all path: $\mathcal{P} = \cup_i \text{P}_\text{i}$
f(P)	Flow of path P
$c_e(\text{F})$	Capacity of the link $e \in \text{F}$, e=(u,v)
T	Period length
J	Energy budget
θ, λ, σ	Dual variables

increases the interferences. On the other hand, power control mechanisms aim at minimizing the transmission powers which can save a significant energy.

A link $e = (u, v)$ is in the configuration F if and only if there exist at least one PRB k such as $(u, v, k) \in \text{F}$. The capacity of the link e in the configuration F is $c_e(\text{F}) = \sum_{k,(u,v,k)\in\text{F}} c_e^k$.

A node v which is involved in no active transmission is said *idle* and denoted $v \notin \text{F}$, for sake of simplicity. The energy cost of an idle node v is $J_{idle}(v)$.

Each feasible configuration F has an energy cost $J(\text{F})$ taking into account the active transmissions and the idle nodes:
$J(\text{F}) = \sum\limits_{(u,v,k)\in\text{F}} \left(j_t^k(u) + j_r^k(v)\right) + \sum\limits_{v\notin\text{F}} J_{idle}(v)$.

Definition 2 At each time, one and only one configuration is active and $w(\text{F})$ denotes the duration of activation of the configuration F. The total length of the period is hence $\text{T} = \sum_{F\in\mathcal{F}} w(\text{F})$.
The total communication cost of the network to route the traffic demand is $\sum_{\text{F}\in\mathcal{F}} w(\text{F})J(\text{F})$.

4.1 Routing and Scheduling

The activation of a configuration F during a time unit provides to each link e a capacity $c_e(\text{F})$. The total link capacity through the period is $\sum_{\text{F}\in\mathbf{F},\text{F}\ni e} c_e(\text{F})w(\text{F})$. This capacity is used to route the traffic from the mesh routers to the gateways.

For each node u, $\mathcal{P}_u$ denotes the set of all possible paths between u and a gateway, and all the possible paths are $\mathcal{P} = \cup_u \mathcal{P}_u$. The traffic flow on the path P is f(P). The traffic sent by u is hence $\sum_{\mathcal{P}_u} f(\text{P})$. The flow over a link e is the sum of the traffic on the path going through e, $\sum_{\text{P}\ni e} f(\text{P})$. This flow has to be below the capacity of e.

The joint routing and scheduling problem is expressed in the two following linear programs (LP): one is capacity oriented, the other one is energy oriented. The first one maximizes the capacity with an energy budget constraint. Let us call the following LP the Master Problem to Maximize Capacity (MPMC):

$$\min \sum_{\text{F}} w(\text{F})$$

$$\text{subject to } \forall r \in V_r \qquad \sum_{\text{P}\in\mathcal{P}_r} f(\text{P}) = d(r) \tag{2}$$

$$\forall e \in E \qquad \sum_{\text{P}\in\mathcal{P},\text{P}\ni e} f(\text{P}) \le \sum_{\text{F}\in\mathbf{F},\text{F}\ni e} c_e(\text{F})w(\text{F}) \tag{3}$$

$$\sum_{\mathrm{F}} w(\mathrm{F}) J(\mathrm{F}) \leq J \tag{4}$$

Objective function imposes the minimization of the time frame needed which maximize the capacity. Equations (2)-(3) express the routing part as a flow from BSs to the gateway. Constraints Eq. (3) impose that the total flow on the link e does not exceed the capacity of the link itself while constraints Eq. (2) ensure that the total traffic received by the gateways and transmitted by the node r equal to the demand traffic of this node. Eq. (4) constrains the total energy expenditure of the network to a budget J while the objective is to minimize the time frame, i.e. to maximize the capacity.

The energy oriented version minimizes the total energy expenditure subject to capacity guarantee. The flow equations are the same as Eq. (2)-(3) while Eq. (5) upper bounds the period length, hence lower bounding the capacity. Let us call the following LP the Master Problem to Minimize Energy consumption (MPME):

$$\min \sum_{\mathrm{F}} w(\mathrm{F}) J(\mathrm{F})$$

subject to Equations (2)-(3) and

$$\sum_{\mathrm{F}} w(\mathrm{F}) \leq T \tag{5}$$

Because the numbers of paths and configurations are exponential with the size of the network, these formulations are not scalable as it is. Column generation [?, ?] is a prominent and efficient technique to cope with this situation. Based on sophisticated linear programing duality results, it allows to save the enumeration of the variable sets. The column generation implemented is described below.

4.2 Column generation

The idea of column generation is to solve a Master Problem with restricted sets of paths $\mathcal{P}_0$ and configuration $\mathcal{F}_0$; $\mathcal{P}_0$ and $\mathcal{F}_0$ have to be carefully chosen to ensure the existence of an initial feasible solution. Generally, $\mathcal{P}_0$ should contain a shortest path from each base station to a gateway, and $\mathcal{F}_0 = \{\{\mathrm{e}\}, \mathrm{e} \in \mathrm{E}\}$. Solving the Master Program generates a set of dual values, described in the following section. Given these values, auxiliary programs described in Section 4.2.2, seek a *column* of the master program (i.e a path or a configuration) violating the corresponding equation of the dual. If such a column exists it may improve the solution, the master program is hence solved using it, and the process loops (Fig. 3).

4.2.1 Dual formulation

We present only the dual formulation of MPMC, the one of MPME being very similar. In this LP, there is a constraint corresponding to each path or configuration variable of the master. We denote $\theta(r)$, $\forall r \in \mathrm{V_{BS}}$ the dual variable associated with constraint Eq. (2), $\lambda(e)$, $\forall e \in \mathrm{E}$ associated with constraint Eq. (3) and σ associated with constraint Eq. (4). O(P) denotes the source node of path P. J_u is the energy consumption of node u which depends on its activity: transmission, reception, or idle.

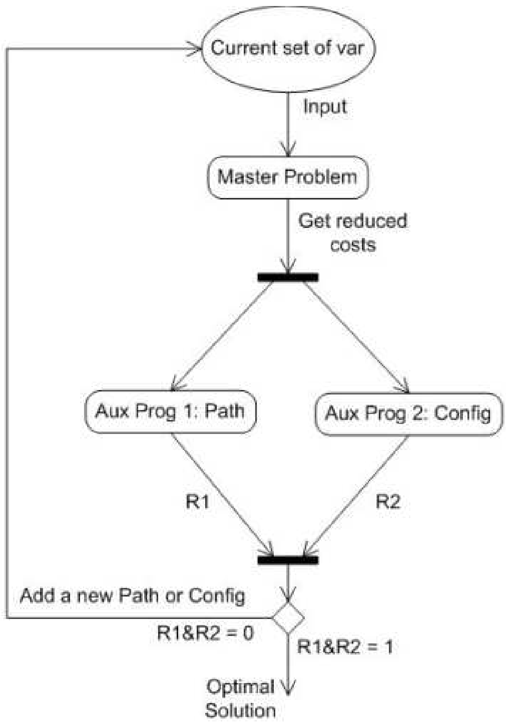


Figure 3: The column generation process

Dual formulation of MPMC

$$\max \sum (\theta(r)d(r)) - \sigma J$$

$$\text{subject to:} \qquad \forall \mathrm{P} \in \mathcal{P} \qquad \theta(\mathrm{O(P)}) \leq \sum_{e \in \mathrm{P}} \lambda(e) \tag{6}$$

$$\forall \mathrm{F} \in \mathcal{F} \qquad \sum_{e} \sum_{k} c_e^k \lambda(e) - \sigma \sum_{u} J_u \leq 1 \tag{7}$$

4.2.2 Auxiliary problems

The auxiliary problems determine if there are paths or configurations that violate the constraints of the dual program. The column generation algorithm involves two such problems, one for each kind of dual constraints. The first one, associated to constraint Eq. (6), finds, for each source node, a weighted path with a weight lower than the dual variable associated to the source node. If the minimum weighted path fits the constraint then all other paths do. This problem is hence solved by any shortest path algorithm or linear program.

The second auxiliary problem is associated to constraint Eq. (7). We need to decide if it exists a configuration such that $\sum_e \sum_k c_e^k \lambda(e) - \sigma \sum_u J_u > 1$. Again, if the maximum weight communication set respects Eq. (7) then all other configurations do.

In this section, we presented our multi-objective linear program and the column generation to solve it. Note that the linear program, associated to constraint Eq.

(7), is generic and can take any interferences and energy model. Its complexity depends on the degree of accuracy of functionalities implemented (interference model, with/without power control and adaptive modulation). The more we detail and we investigate deeply in our study, the more the complexity and the compute time becomes very high. In the next section, we start with a simple interference model without power control to give some preliminaries results about the tradeoff between capacity and energy consumption. More realistic scenarios are studied in the next sections.

5 Fixed Transmit Power Model and Single Modulation and Coding Scheme

In this section, we present the auxiliary program to generate a new configuration if the constraint Eq. (7) is violated. We assume that the power transmission and the modulation and coding scheme are fixed for each base station. We assume also a binary interference model: transmissions have to be pairwise non interfering, i.e. on non-conflicting links or on distinct PRBs. Note that these assumptions minimize the realistic of our scenario but greatly reduce the complexity and the time to calculate an optimal solution.

5.1 Generation of configurations

Given a topology, the problem is hence to find a configuration F $\in \mathcal{F}$ where $\sum_e \sum_k c_e^k \lambda(e) - \sigma \sum_u J_u$ is maximum on F. To compute such a configuration, with interferences and energy consumption models, we develop the following Mixed Integer Linear Program. The binary interferences is modeled by constraint Eq. (11), a link e cannot be active in conjunction with a link $e' \in I_e$ (set of links that interfere with e). The energy consumption model takes into account the cost of the nodes transmitting or receiving Eq. (9), and the consumption of idle nodes (10). Finally, $z(e,k)$ is a binary variable associated with the link e: $z(e,k)$ =1, if link e at scheduling block k belongs to the new configuration and 0 otherwise.

$$\max \sum_{e \in E} \sum_{k} (c_e^k \lambda_e) - \sigma \sum_{u} J_u \tag{8}$$

$$\forall u, v, k \qquad J_u \geq \sum_{k} \sum_{v} (T_s * P_t^k(u) z(u,v,k) + j_r^k(v) z(v,u,k)) \tag{9}$$

$$\forall u \qquad J_u \geq J_{idle}(u) \tag{10}$$

$$\forall e \in E, e' \in I_e, k \in [1,K] \qquad z(e,k) + z(e',k) \leq 1 \tag{11}$$

$$z(e,k) \in \{0,1\}, \forall e \in E \tag{12}$$

5.2 Scenarios and Model Parameters

Both the capacity-oriented and energy-oriented formulations, and the column generation algorithm have been implemented and tested using AMPL/CPLEX. For simplicity and without lost of generality, we assume that for each base station the average signal-to-noise ratio (SNR) equals to 22dB, and the noise power density is -174 dBm/Hz. All base stations operate at the same transmit power, and use the same modulation (QPSK). The channel attenuation is modeled by a path-loss with an exponent of 2.6

(Line Of Sight channel model). The radio parameters of LTE system are used (presented in Section 3.1).

We consider grid network topologies and random one composed of $\{9, 24, 49, 121\}$ nodes, where only one gateway is located in the network center. The upload traffic in the network is uniformly distributed among the nodes.

5.3 Network capacity, Energy cost and scalability

We present, firstly, the evolution of the minimal energy consumption and the maximal capacity according to the network size (from 9 to 121 nodes) (see Fig. 4). It confirms the result of a decreasing capacity when the network size increases [?] whereas the energy consumption increases with the number of stations in the network. Adding new base stations increases the traffic load in the network, and thus, both the period length and the energy consumption increase. This explains the decreasing capacity and the increasing energy consumption.

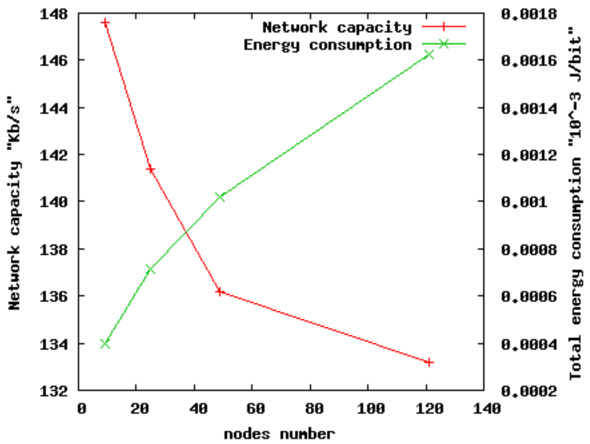


Figure 4: Capacity and energy consumption evolution vs size of the network

5.4 Capacity and energy trade-off

If the previous result highlights the behavior of the energy consumption and the capacity according to the network size, we can not conclude anything about a possible trade-off between energy and capacity. Nevertheless, in figure 5 we provide the capacity/energy Pareto front in the case of a random network topology (49 eNodeB's). Note, that in this scenario, we do not take into account the idle energy consumption. First, we note the existence of a minimal value of energy required to meet the capacity constraint: it means that if less energy is available, the traffic demand can not be routed. Second, the capacity tends to an asymptotical boundary. Between those two points, the capacity increases slightly with the energy consumption.

Note that, by using a binary interference model, the spatial reuse is free and does not impact the trade-off: there is no additional energy cost of the simultaneous links activation. In fact, the overall activated links and the routing are constrained by the energy budget: by increasing the energy budget the routing freedom degrees increase. Indeed, multi-path with different lengths can be used to improve the capacity.

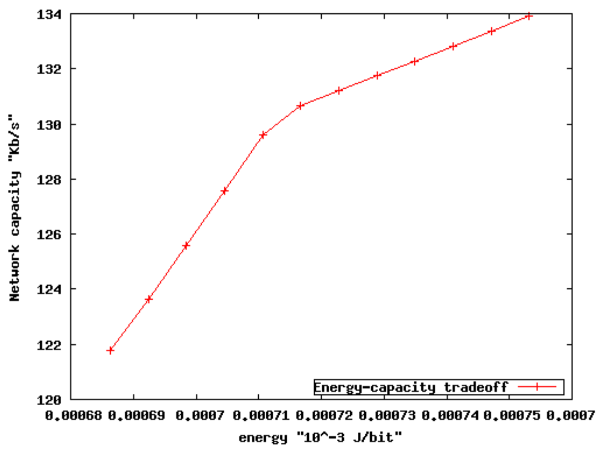


Figure 5: Capacity and energy trade-off, assuming Idle cost = 0.

6 Energy - Capacity Tradeoff and Physical layers parameters

In this section, we improve the second auxiliary program by including a more realistic interference model based on SINR with fine tuned power control at each node. This allows us to investigate deeply on the capacity/energy tradeoff and to study the impact of physical layer parameters such as the SINR threshold and the path-loss exponent on these metrics. In fact, maximizing the number of simultaneous transmissions for each scheduling block, allows to minimize the scheduling period T (total slot number) hence to maximize the capacity. Unfortunately, this happens at the cost of an increase of the total transmission power because maximizing the concurrent transmissions increases the interferences. The most power efficient schedule would be the one where every transmission has its own scheduling block.

6.1 SINR interferences with adaptive power

This linear program is similar to the last one but with SINR interferences model. Given a set of dual variables (λ_e, σ) obtained from the master problem (MPME or MPMC), we can generate a new configuration by solving the following Mixed Integer Linear Program:

$$\max \sum_{e\in E}\sum_{k}(c_e^k\lambda_e) - \sigma\sum_{u} J_u \tag{13}$$

$$\forall u,v,k \qquad J_u \geq \sum_{k} T_s * P_t^k(u) + \sum_{k}\sum_{v} j_r^k(v)\Psi_{(v,u),k} \tag{14}$$

$$\forall u \qquad J_u \geq J_{idle}(u) \tag{15}$$

$$\forall u,k \qquad \sum_{v}\Psi_{(u,v),k} + \sum_{w}\Psi_{(w,u),k} \leq 1 \tag{16}$$

$$\begin{aligned}\forall u,v,k \qquad P_t^k(u) * L(u,v) \geq \beta * (&\sum_{(u',v')\neq(u,v)} P_t^k(u') * L(u,v) \\ &+\mu) - (1-\Psi_{(u,v),k})nP_{max}\end{aligned} \tag{17}$$

$$\forall u, k \qquad P_t^k(u) \leq P_{max} \tag{18}$$

The constraint Eq. (17) ensures that the SINR threshold is satisfied for all active links belong to the configuration. Recall that an interference will occur only when more nodes are allocated to the same scheduling block at the same time slot. Constraints Eq. (16) implies that each node is active in at most one link in each scheduling block. $L(u,v)$ is the attenuation function and equal to $d(u,v)^{-\alpha}$ in our study. Finally, $\Psi_{(u,v),k}$ is a binary variable associated with the link (u,v) at the PRB k. If $\Psi_{(u,v),k} = 1$ then the link (u,v) is active with the PRB k in the new configuration. Note that $(1 - \Psi_{(u,v),k})nP_{max}$ is equal 0 when the link (u,v) belongs to the new configuration ($\Psi_{(u,v),k} = 1$), hence the constraint Eq. (17) reverts back to the classical interferences constraint Eq. (1). Otherwise ($\Psi_{(u,v),k} = 0$), nP_{max} ensures that $P_t^k(u) = 0$.

6.2 Impact of physical layer parameters

We investigate the sensitivity of the network capacity and the energy consumption to the SINR threshold variation (from 1 to 70). For each SINR value, the minimum time frame and the total energy consumption are reported on Fig. 6. One can remark that the time frame is a step function while the energy consumption grows at each step. Considering the impact of the SINR on a given configuration gives an insight on this behavior. Let us consider an admissible configuration with SINR 1. Increasing the SINR threshold, all links can be kept active by increasing the transmission power to mitigate the sensitivity to interferences. This energy cost explodes as the interferences get too strong. Once this step is reached, some links have to be deactivated which results in an increase of the time frame and a decrease of the energy consumption.

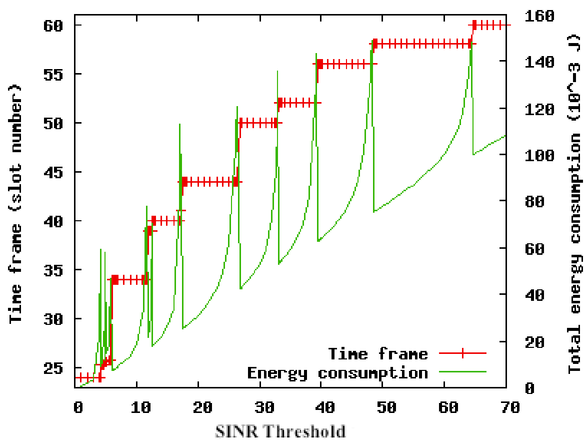


Figure 6: Energy consumption and time frame vs SINR threshold.

In Fig. 7, we study the same scenario under the following assumptions: the SINR threshold is set to 10, the idle node consumption equals to 40% of the reception cost, the path loss exponent varies between 2 (ideal empty 2D space) and 4.5 (indoor environment with many obstacle or very dynamic). It shows an exponential growth of the overall energy consumption. BS position have significant impact on the energy consumption: a BS located in a perturbed environment consume much more than one situated in a ideal environment.

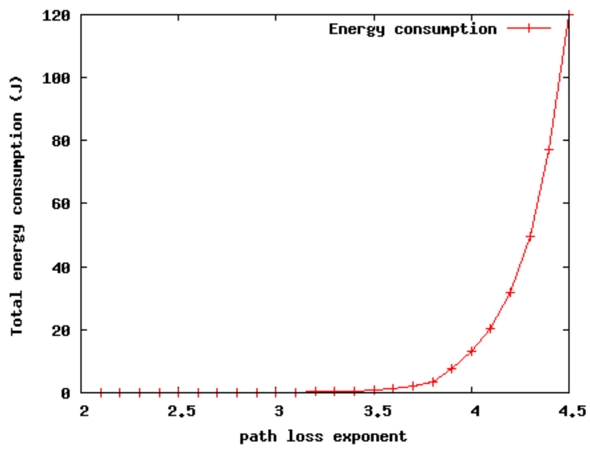


Figure 7: Energy consumption vs path loss exponent: : Idle=0.4*RX .

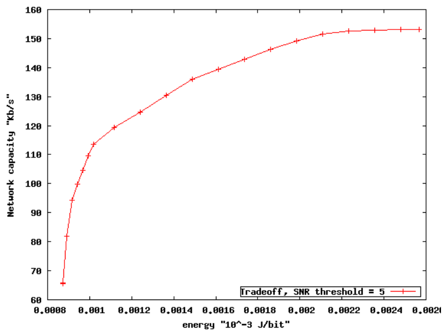
6.3 Capacity and energy tradeoff

The Pareto front of the capacity/energy tradeoff, when the consumption of idle nodes is null, is depicted in Fig. 8 for some fixed MCS. Note the requirement of a minimal energy budget for the network to route all the traffic demand. Optimizing the capacity needs to maximize the spatial reuse in the configurations, with a transmission power cost in order to mitigate the resulting interferences. This is confirmed by the evolution of the mean cost of a transmission with the density of the configurations, reported in Fig. 10 (see `link_cost without idle cost`). Note that the magnitude of the tradeoff is increased compared to the previous scenario presented in section 5.4. In fact, the binary interference model with fixed power is very limited: there are not many tuning parameters which can increase the tradeoff. While using a SINR interference jointed to power control can increase or reduce the spacial reuse (hence the interference) which increases the gap of the tradeoff.

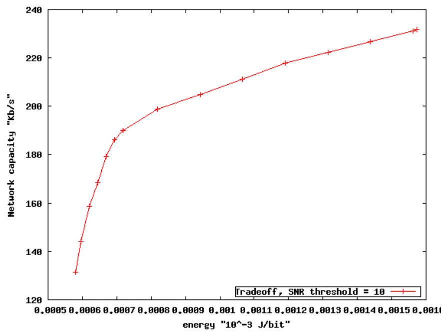
We also investigate an idle energy consumption varying from 20% to 100% of the reception cost. It adds a penalty on the energy consumption for each non transmitting node, which is an energetic incentive for spatial reuse. Consequently, the strategy for minimizing the energy consumption is twisted to the one for increasing the capacity. The magnitude of the energy-capacity tradeoff corresponding to the idle energy cost is reported as Fig 9. As expected, the tradeoff disappears as the consumption of idle nodes grows. Again, the behavior of the mean cost of a transmission with the configurations density, reported in Fig. 10, confirms this fact. Indeed, the total consumption of the idle nodes is shared among the cost of the active transmissions, and this total reduces as the cardinality of the configuration increases. When the consumption of idle nodes is significative (20% is enough), the mean cost of a transmission decreases with the density of the configurations.

7 Adaptive modulation and optimal system configuration

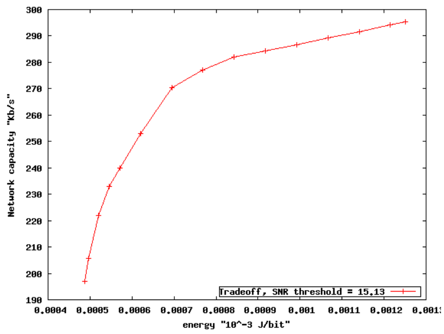
In this section, we study the joint allocation of MCS, scheduling bloc and power transmission to maximize the capacity and minimize the energy consumption. Our goal is to calculate an optimal system configuration of the network: choice of nodes parame-



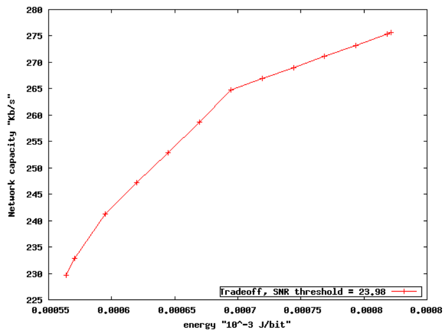
(a) β=5, BPSK, CR=1/2, 164Kb/s



(b) β=10, 16QAM, CR=1/2, 328.12Kb/s



(c) β=15.13, 64QAM, CR=1/2, 492.18Kb/s



(d) β=23.98, 64QAM, CR=3/5, 590.625Kb/s

Figure 8: Capacity and energy tradeoff, assuming Idle cost = 0.

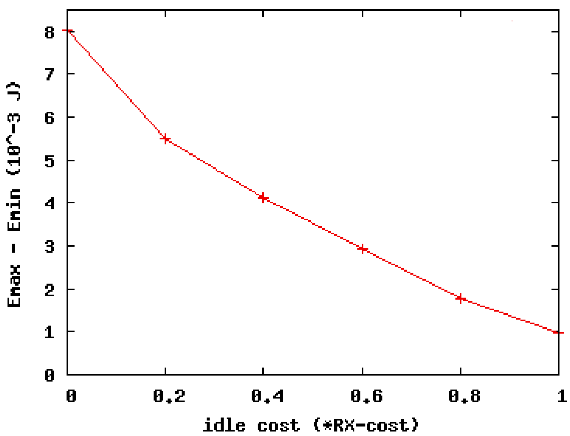


Figure 9: Capacity and energy tradeoff.

ters like the modulation, the coding, the routes for data, the power transmission, the resources allocation and the link schedules.

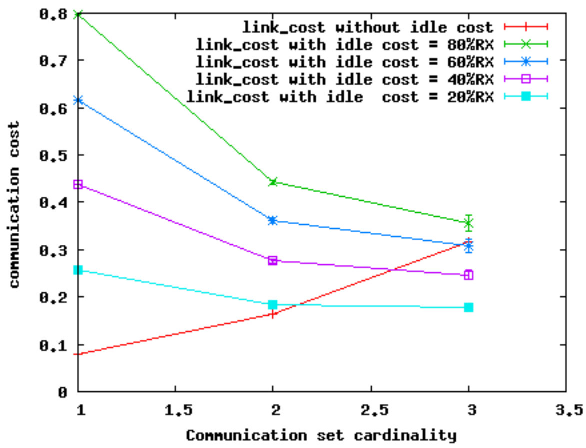


Figure 10: Communication cost vs transmission set size.

Definition 3 Given a set of $\{MCS_j\}$ associated to a set of SNR threshold $\{\beta_j\}$ and capacity $\{c_j\}$, $j \in [1..N_c]$. We define a class denoted S_j the indexed collection $\mathrm{S}_j = (MCS_j, \beta_j, c_j)$, $\mathcal{S} = \cup_j \mathrm{S_j}$.

Given a configuration F, each communication $(u, v, k) \in$ F is activated during $W(\mathrm{F})$ with S_j which provides the throughput $c^k_{(u,v)}$. An optimal system configuration consist in finding for each communication the best S_j with a minimum transmission power that minimize the overall energy consumption and maximize the network capacity. The main questions to be addressed is how S_j are to be distributed to communications and how much power is to be reserved to each node.

In this work, we interest to five different MCS presented in the Tab. 3. We see that the energy consumption and the capacity are linked to the MCS used. In fact, the modulation and the coding rate require to adjust the transmission power to adapt to the instantaneous channel quality. Intuitively, higher modulation means higher throughput and capacity but require more power transmission to meet the SNR threshold constraint. This stresses on the trade-off between capacity and energy consumption.

To further illustrate this trade-off, we study a simple scenario of a communication between a source and destination, with a distance of 83m, a traffic demand of 10 packets and a noise power density of -174 dBm/Hz. The minimum power transmission needed to achieve a MCS_j is presented by Tab. 4. Basing on these energy efficiency values, we observe that MCS1 is the most energy efficient but it is the lowest in capacity while MCS5 gives the best capacity. Fig. 11 illustrates the throughput and the minimum energy consumption per bit corresponding to power transmission.

Under this scenario with an isolated link, transmitting power and throughput are bound by the MCS characteristics which results in a trade-off on the energy efficiency. As seen in Section 6, in a scenario with several nodes and concurrent communications, the interferences and the spatial reuse induce a trade-off between the overall energy consumption and capacity. In the following, we study the combination of these two trade-offs in a network with adaptive modulation and power control enabled nodes.

7.1 Adaptive modulation joint power control

We extend the previous auxiliary program presented in 6.1 to include the adaptive MCS. In this case, the source nodes of all communications can choose the best of N_c class and transmit with adaptive power depending on the SINR achieved at the

Table 3: Modulation and Coding Schemes: MCS

MCS	Modulation	CR	β	Throughput	Efficiency
MCS1	QPSK	1/2	1.259	164 Kb/s	0.911 b/s/Hz
MCS2	16QAM	1/2	10	328.12 Kb/s	1.82 b/s/Hz
MCS3	16QAM	3/5	13.80	393.75 Kb/s	2.18 b/s/Hz
MCS4	64QAM	1/2	15.13	492.18 Kb/s	2.73 b/s/Hz
MCS5	64QAM	3/5	23.98	590.625 Kb/s	3.28 b/s/Hz

Table 4: MCS Vs transmission power on a link

MCS	Power	Energy Efficiency
MCS1	0.004919 W	3 10^{-8} J/bit
MCS2	0.039059 W	119 10^{-8} J/bit
MCS3	0.053895 W	137 10^{-8} J/bit
MCS4	0.059089 W	12 10^{-8} J/bit
MCS5	0.093651 W	16 10^{-8} J/bit

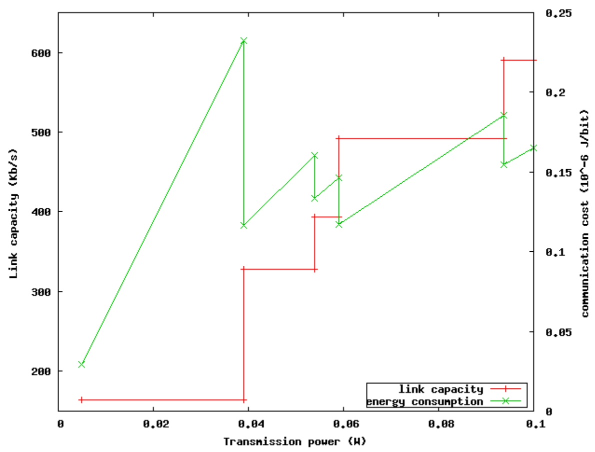


Figure 11: Capacity and energy consumption versus transmission power on a link.

receiver. Note that the previous model is a particular case of this one when $N_c = 1$. The subproblem can now be modeled as follows:

$$\max \sum_{e \in E} \sum_{k} (c_e^k \lambda_e) - \sigma \sum_{u} J_u \tag{19}$$

$$\forall u, v, k \qquad J_u \geq \sum_{k} T_s * P_t^k(u) + \sum_{k} \sum_{v} \sum_{l} j_r^k(v) \Psi^l_{(v,u),k} \tag{20}$$

$$\forall u \qquad J_u \geq J_{idle}(u) \tag{21}$$

$$\forall u, v, k \qquad c_e^k = \sum_{l} (C_l - C_{l-1}) \Psi^l_{(u,v),k} \tag{22}$$

Table 5: Scenarios and parameters

Topology	Random/Grid network, 25 nodes
Traffic demand	Uniform, Random uniform, Poisson
Path loss exponent	2.6
Noise power density	-174 dBm/Hz
Scheduling block size	1ms/180 Khz

$$\forall l, (u,v) \in E, k \qquad \Psi^{l-1}_{(u,v),k} \geq \Psi^{l}_{(u,v),k} \tag{23}$$

$$\forall u, l, k \qquad \sum_{v} \Psi^{l}_{(u,v),k} + \sum_{w} \Psi^{l}_{(w,u),k} \leq 1 \tag{24}$$

$$\begin{aligned} \forall u, v, k, l \qquad P_t^k(u)\frac{1}{d(u,v)^\alpha} \geq \beta_l * (&\sum_{(u',v') \neq (u,v)} P_t^k(u')\frac{1}{d(u',v)^\alpha} \\ &+\mu) - (1 - \Psi^{l}_{(u,v),k}) n P_{max} * Cst \end{aligned} \tag{25}$$

$$\forall u, k, l \qquad P_t^k(u) \leq P_{max} \tag{26}$$

Constraint Eq. (22) ensures that each communication (u,v,k) can communicate with a capacity (C_l) associated to the class number l and choosing from the finite set $\{C_l\}$, $l \in [1..N_c]$. Recall that $\Psi^{l}_{(u,v),k}$ is a binary variable associated with the communication (u,v,k) at the class number l. If $\Psi^{l}_{(u,v),k} = 1$ then the communication (u,v,k) is active in the new configuration with the class number l.

7.2 Setting for Numerical Results

In this section, we present numerical results that validate the efficiency of the solution procedure and offer additional insights. In this study we are interested on many network scenarios and different models of traffic demand presented in Tab. 5 with others parameters of our scenarios study. Note that the different class presented in Tab. 3 and radio parameters of LTE system (presented in Section 3.1) are used. For each network, an optimal solution is calculated: network capacity, energy consumption, routing, resource allocation, physical parameters of each node (transmission power and MCS used for each time-frequency block), period T and activation time of each communication.

7.3 Optimal capacity and energy consumption: Adaptive power Vs fixed power

We start our study with a grid of 25 nodes with a gateway at the center and with uniform demand traffic. Let P_1 be the minimum power to satisfy the SNR threshold β_1 and P_{N_c} the minimum power to satisfy the SNR threshold β_{N_c}. Two scenarios have been studied. The first one consider fixed power case: all active nodes transmit with a fixed power P_{Fixed} which varies between P_1 and $P_{max} \geq P_{N_c}$. The second one consider the control power case : each source node u transmit with a power $P_t(u) \leq P_{Fixed}$. For each value P_{Fixed}, we compute the optimal network capacity and its related minimum energy consumption.
Fig. 12 and Fig. 13 illustrate, respectively, the optimal network capacity and the total energy consumption as a function of the transmission power. It can be seen that

the network capacity increase by step with the transmission power. Obviously, the minimum and the maximum capacity are obtained, respectively, with the lowest and the higher transmission power: since increasing the transmission power allows the use of the high modulation (high throughput). Fig. 13 shows that the energy consumption increase with the power transmission and the minimum energy consumption is obtained when only MCS1 is used (the best energy efficiency, Tab. 4).
Comparing the two scenarios (with/without power control), it is obvious that there is a big advantage of the power control. It can be seen that the network capacity is higher and the energy consumption is very low in the case of the power control. We can see that in the case of fixed power, the network capacity is always constant between two MCS levels: Given a fixed number of available class (S_j), increase the power transmission does not impact the optimal capacity but increase the energy consumption. In this case, the only parameter that can improve the capacity is the number of classes available. In the case of power control, the optimal capacity increase between two MCS $[MCS_j, MCS_{j+1}]$ thanks to spatial reuse. In fact, by adjusting the transmission power the interferences between communications can be reduced, this allows more spatial reuse and hence increases the network capacity.
To conclude, using a power control the network capacity can be improved by using a high modulations and by increasing the spacial reuse. While in the case of fixed power only the high modulations can increase the capacity because by increasing the fixed transmission power, the SINR at receivers is almost constant which result a fixed spatial reuse. Note that in the case of a fixed power, the use of high modulations can minimize the reuse spatial to ensure the SINR constraint.

7.4 Energy and Capacity Tradeoff

The tradeoff between energy consumption and network capacity is depicted in Fig. 14 and Fig. 15 which present, respectively, the scenarios of power control and fixed power. In this study, the maximum power transmission is set to 0.1 Watt which allows to use any MCS. That is means for the fixed power scenario, all sources nodes transmit with 0.1 watt while in the power control scenario the transmission power $P_t(u) \leq 0.1$.

Fig. 14 and Fig. 15 show an important tradeoff between capacity and energy consumption. This tradeoff is the result of the use of different MCS and the impact of the spatial reuse. The efficiency energy is when only one communication is activate in a time slot using MCS1, in this case the capacity is very low. Increasing the number of simultaneous communications and using high modulations increase the capacity but consume more energy.

Comparing the energy-capacity tradeoff obtained with the two scenarios, we see that in the fixed power transmission case the capacity increases rapidly when the power transmission is high. This mean that is more efficient to use the high power transmission. In the power control case, we see that the capacity increases rapidly when the power transmission is low. This shows that is more efficient to use the low power transmission.

7.5 Capacity and energy distribution

In this study, we ask about the capacity sharing and the distribution of the energy consumption in the network. We ask about the strategy of MCS allocation between the nodes. This allows us to move from the optimization towards develop a protocol based on the strategy of the optimal solution. In this section, we present only the capacity and energy consumption distribution.
Fig. 16 and Fig. 17 present, respectively, the throughput and the energy consumption of each node to send its own traffic and to route the traffic of the other nodes. Note that these results are for the case of grid topology with power control. It can be

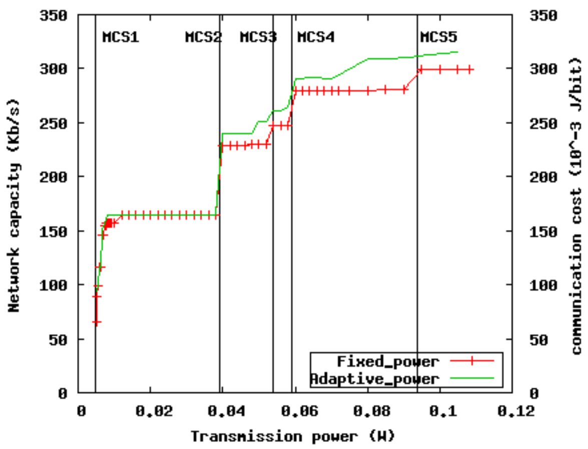


Figure 12: Network capacity: power control Vs fixed power

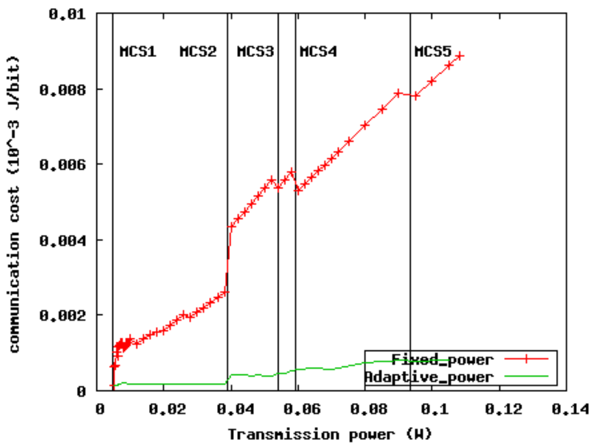


Figure 13: Energy consumption per bit: power control Vs fixed power

seen that the gateway and the nodes around it are the most consumer of energy and bandwidth. This can be explained by the fact that all traffic in the network are routed by these nodes and hence they need more bandwidth and energy consumption.

8 Impact of traffic demand and topology

The previous results have been obtained in the case of grid network with uniform traffic demand. To further illustrate our study, we present in this section the energy-capacity tradeoff with different model of topologies and traffic demands.

8.1 Impact of topology

In addition to the grid topology, two other kinds of topologies have been studied. The first one is a random network where 25 nodes are randomly distributed in the Euclidean plan with a gateway in the center (marked as a white node). This network is shown in Fig. 18(a). The second one is based on a urban network. The nodes are

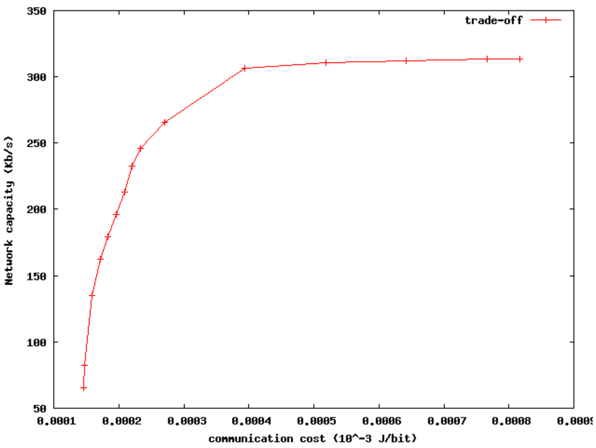


Figure 14: Energy and capacity tradeoff: power control, grid topology

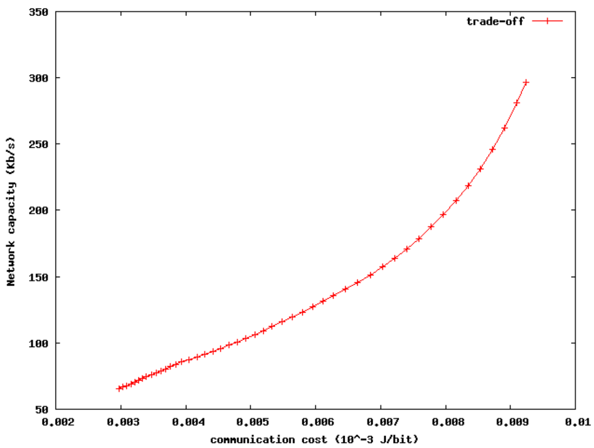


Figure 15: Energy and capacity tradeoff: fixed power, grid topology

placed in a cross-street with a gateway in the intersection and with fixed inter-node distance, Fig. 18(b). In all of these scenarios, the path loss exponent $\alpha = 2.6$.

The impact of the topology is illustrated by Fig. 20(a) and Fig. 20(d). For the two scenarios (fixed power and power control case), the three curves (grid, random and urban network) evolve in the same way but with different interval and slope. The urban network have the highest capacity compared to the others. This can be explained by the fact that in this network the interference phenomenon is limited especially around the gateway compared to the others (low nodes density). This can increase rapidly the capacity and minimize the energy consumption which explains the low magnitude of the tradeoff. By analyzing the results of the three topologies, we deduce that the magnitude of the energy-capacity tradeoff depends on the nodes density. In fact, when the density is high, the magnitude of the energy-capacity tradeoff increases (random network case): the interferences constraints will be very hard between the communications, hence the energy consumption increases.

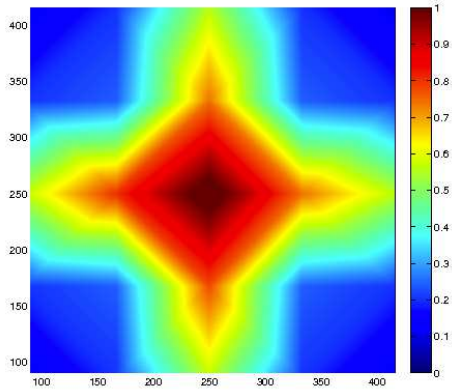


Figure 16: Energy distribution

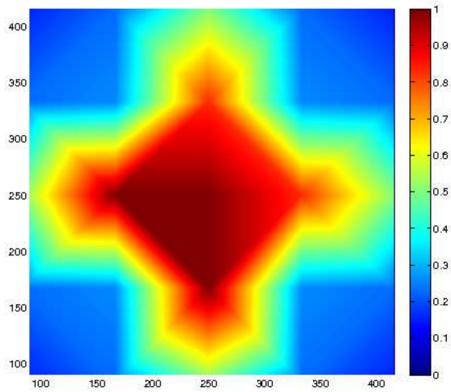


Figure 17: Capacity distribution

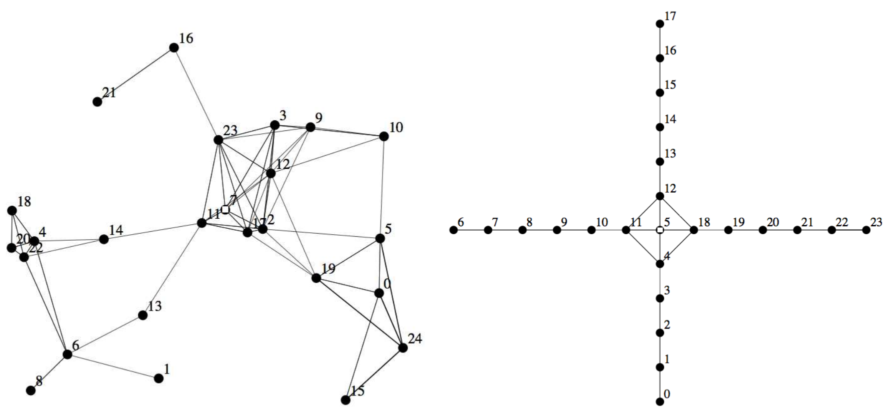
8.2 Impact of traffic demand

We study here the impact of the traffic demand on the energy-capacity tradeoff. The traffic demand studied are:

- Uniform demand: all nodes in the network have the same traffic demand.
- Poisson demand: the traffic demand is distributed according to a Poisson law.
- Uniform random demand: the traffic demand is distributed according to a Uniform law.
- Arbitrary demand: the traffic demand is arbitrarily distributed.

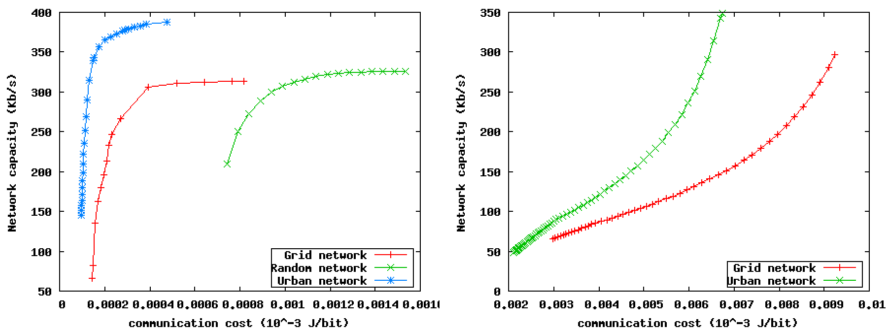
The small influence of the traffic demand is illustrated by the Fig. 20 which presents the energy-capacity tradeoff according to traffic demand in the case of grid/urban network and fixed/adaptive power. It can be seen that the impact of the traffic demand distribution on the energy-capacity tradeoff is very low. In fact, the traffic demand distribution in the outside is not very important but only the bottleneck zone around the gateway have the more decision on the capacity.

We also studied the case of high demand traffic concentrated in a zone (bottleneck zone) and low demand for the rest of nodes. This scenario is studied for two cases, the



(a) Random topology (b) Urban topology

Figure 18: Network with 25 nodes



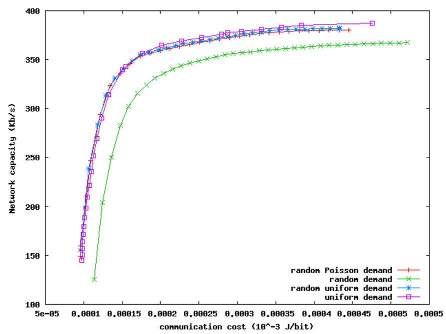
(a) Random topology (b) Urban topology

Figure 19: Capacity and energy tradeoff, assuming Idle cost = 0, with power control and adaptive modulation.

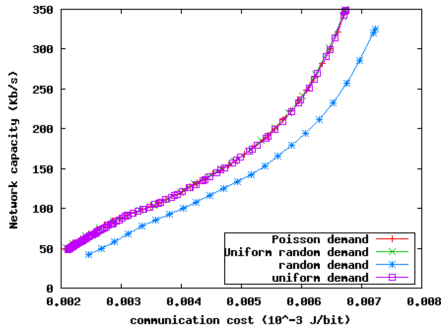
first one illustrated by Fig. 21(a) which presents the case of a gateway in the center (classic scenario). The second one is when the gateway is located in the grid corner, see Fig. 21(b). It is shown that the impact of the traffic distribution is significant when the distribution of the traffic demand is located in a point. We also deduce an impact of the distance between the bottleneck and the gateway: the capacity and the energy consumption is better when the bottleneck is near the gateway.

9 Discussion

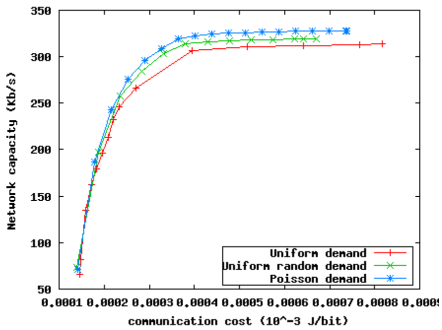
In this section we discuss about the main contributions of this paper and we compare with others works. This discussion is divided in two parts: the first is about the multi-objective framework which we developed. The second part is about the mains results of this paper.



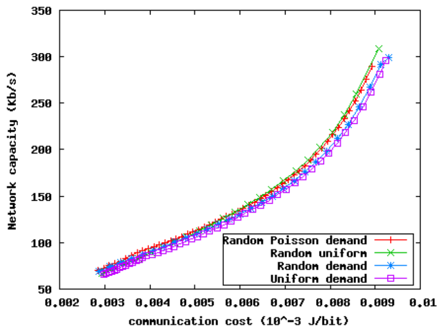
(a) Urban topology, power control



(b) Urban topology, fixed power

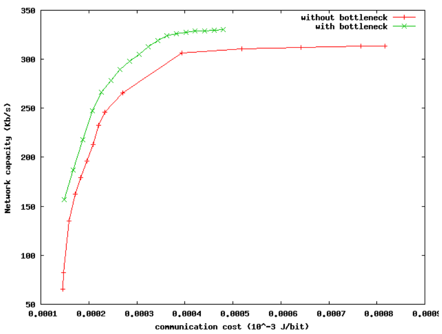


(c) Grid topology, power control

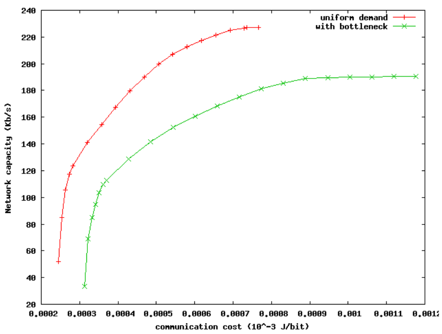


(d) Grid topology, fixed power

Figure 20: Capacity and energy tradeoff, assuming Idle cost = 0, with power control and adaptive modulation.



(a) Grid topology, gateway in the center



(b) Grid topology, gateway in the corner

Figure 21: Capacity and energy tradeoff, assuming Idle cost = 0, with power control.

9.1 Multi-objective optimization framework

In this work we have presented an extensible multi-objective framework based on a linear program model and columns generation algorithm. This optimization model is generic and can take any interferences and energy model. We recall that the complexity of this framework depends on the degree of accuracy of functionalities implemented. The more we investigate deeply in our study, the more the complexity becomes very high. For example, the compute time to study a scenario with adaptive modulation (Section 7.3) is very high compared to the scenario with binary interference (Section 5). A deeper challenge is to minimize this complexity to cope with larger network size.

Compared to the frameworks presented in the literature, our developed tools are generic and have more functionalities and advantages. In [?, **?**], a linear programming models of wireless mesh networks have been developed in order to compute a joint optimal resource allocation and routing. The authors use a binary interference model with fixed power and single frequency. This work is extended in [?] by using a SINR interference model and variable transmission rate. All these works are only limited in the capacity optimization with a single frequency assuming a time division multiple access (TDMA). The framework we contribute is based on a multi-objective linear program and allows both, maximizing the capacity and minimizing the energy consumption. Moreover, our tools can be applied to any synchronous slotted technology in which the resource is divided into time-frequency elements. Note that the TDMA is a particular case for our study using a single PRB (single frequency). In addition to that, we use more realistic for the physical layer by including a SINR interference model with fine tuned power control and adaptive modulation.

9.2 Network Results

Several works in the literature have focused on maximizing the capacity or minimizing the energy consumption, but investigating the tradeoff between them has received relatively less attention. The study of this tradeoff has been one of the main results presented in this paper. We have seen that the magnitude of the energy-capacity tradeoff increase: firstly, when we included a SINR interference with power control (Section 6). Secondly, when we added an adaptive modulation (Section 7.3). For all scenarios, it is shown that there is no significant tradeoff between capacity and energy when the power consumption of idle nodes is important. [**?**] has discussed under which circumstances energy efficiency and throughput can be jointly maximized, and when they constitute different objectives. In the context of p-persistent CSMA based WLAN, it was shown that power saving and throughput do not constitute different objectives and can be jointly achieved. [?] prove that this is not always true and they can constitute different objectives. The advantages of the power control and adaptive modulation have been shown in section 6 and 7.3. The power control allows to maximize the capacity and to minimize the energy consumption by reducing the power transmission and the interferences. This confirms the results of [?, ?, **?**] which shows that the power control improves the spatial reuse and hence minimize the frame time.

10 Conclusion

In this paper, we have addressed the problem of network capacity and energy consumption optimization. We have presented an novel linear programing model using a column generation algorithm which computes a linear relaxation of the Routing and call Scheduling Problem with a realistic SINR model and power control. This tool can be used in any broadband wireless mesh networks where the resource is divided into time-frequency elements. We have carried out a deeply study of the tradeoff between network capacity and energy consumption using SINR model with a fine tuned power control at each node. We showed that the capacity and energy efficiency can be jointly maximized when the power consumption of idle nodes is important. We also investigated the problem of the allocation of MCS, scheduling block and transmission power to find an optimal system configuration of the backhauling network. We also study the impact of the power control, traffic demand and topology on network performance. A deeper challenge is to develop a protocol or distributed algorithm based on the results of our study which provides high network capacity with efficiency energy consumption.

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